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Predicting user perceived satisfaction and reuse intentions toward Massive Open Online Courses (MOOCs) in the Covid-19 pandemic: An application of the UTAUT model and quality factors



Qing Wang^(a) Muhammad Saqib Khan^{(b)*} Muhammad Kamran Khan^(c)

^(a)School of Economics and Management, Huazhong Agricultural University, Wuhan, 430072, P.R.China

^(b)School of Management, Huazhong University of Science and Technology 1037, Luoyu Road, Wuhan, 430074, P.R.China

^(c)Bacha Khan University, Charsadda, Pakistan

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ABSTRACT

The Covid-19 pandemic restricted the people around the world's boundaries. Therefore, online learning's importance increased in the current era, an essential topic for current research. Students are actively using Massive Open Online Courses (MOOCs) while restricted at their homes during the Covid-19 pandemic. This research investigates the Unified Theory of Acceptance and Use of Technology model (UTAUT) and quality factors to predict the users' perceived satisfaction and reuse intentions toward MOOCs in the Covid-19 pandemic. We collected data from three public universities in Wuhan, China and 298 users who were actively using MOOCs participated in this research. The proposed hypotheses were tested by using PLS-SEM. The findings revealed that effort expectancy and social influence directly impacted users' reuse intentions while performance expectancy and perceived course quality positively impacted users' reuse intentions through perceived satisfaction toward MOOCs. This research found the critical role of perceived satisfaction in the current pandemic era. Finally, this research provides important theoretical implications for the researchers and practical implications for the developers, technologists, and policymakers for developing effective systems and strategies in online environments. In addition, this study revealed some limitations and future research guidelines for the researchers.

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Introduction

The novel *Coronavirus* wave has changed the world dynamics, and every industry affected due to the Covid-19 pandemic, especially the education sector. Consequently, 1.6 billion learners affected worldwide in which 9/10 students suffered due to quarantines and school shutdowns are still applicable. Such consequences gained researchers' attention to review online learning methods and technology studies, providing valuable knowledge and covering this gap during the Covid-19 pandemic (Yee & Abdullah, 2021). After the Coronavirus outbreak, "Suspension of Classes and Non-stop Learning" is a new system introduced by MOE (Ministry of Education) China to handle the situation either through postponement of a semester or continue online learning during the Covid-19 pandemic. Since May 2019, about 1454 Chinese colleges have used online tutoring platforms to address the pandemic situation, and 17.75 million students have used online platforms for online learning (Cao et al., 2021).

MOOC (massive open online course) is the advanced and innovative online educational system developed over the past eight years (Huang et al., 2017). This system changed the teaching and learning practices at university and at school level and has a big revolution in academia in recent years. The progress of the MOOC gradually reveals its motivating strength in higher education. Universities worldwide participated in the MOOC movement, and several MOOC platforms and projects have been initiated (Jung & Lee, 2018). A recent report published by MOE, China, revealed that universities introduced more than 10 MOOC platforms, and over 460 colleges or universities initiated more than 3,200 massive online open courses. Therefore, 55 million students used this system, and more than 6 million students achieved MOOC credits at the university level (Wan et al., 2020). These activities have shown the rapid

* Corresponding author. ORCID ID: 0000-0002-7722-1018

developments in massive learnings through online platforms. However, some earlier research revealed the low retention rate or continuation in usage, such as Breslow et al. (2013) found less than 5% completion rate of MOOC (name as 6.002x). Jordan (2014) found about a 10% completion rate in most online courses. Similarly, Shao (2018) found a 3.7% completion rate in MOOCs platforms. Therefore, such reasons motivate the researchers to investigate this topic in a broader way. Generally, learners' initial involvement is the first step in the successful application of a MOOC program. The continued participation and use by users is the key motivation for their ultimate success. For instance, although many students are motivated to the new medium instruction and perfect MOOC functions that help them decide to participate and then get the knowledge to improve their productivity and performance. However, due to environmental factors or personal reasons, they somehow quit learning, leading to a low completion rate.

With the combination of eight theories TAM (technology acceptance model), IDT (innovation diffusion theory), TPB (theory of planned behavior), TRA (Theory of Reasoned Action), MM (Motivational model), a model combining TAM and the Theory of Planned Behavior, SCT (Social Cognitive Theory), and MPCU (Model of Personal Computer Utilization), Venkatesh et al. (2003) developed a UTAUT (the unified theory of acceptance and use of technology) model. Similar research revealed that the UTAUT model better explains the user's continued intentions, even up to 70% usage intentions (Venkatesh et al., 2003). However, it still has some limitations. For instance, if students feel that MOOC is easy to use and useful, but if results are not according to their learning requirements. They may give up their usage (Goodhue, 1995). The importance of the UTAUT model is increasing in the present era. Past research mainly focused on investigating the UTAUT model in MOOCs perspective (Altalhi, 2020; GovindAarajan & Krishnan, 2019; Nasef et al., 2019) and also focused on participation and user behavioral intentions toward MOOCs (Barak et al., 2016; Mulik et al., 2018; Zhang, 2016). However, according to the authors' understanding, no empirical research is analyzed with the combination of the UTAUT and perceived course quality (SERVQUAL) factors to predict user satisfaction and reuse intentions. Quality is considered dominant for the success of any MOOC. Many students and learners consider the quality content as are most important while participating in the higher education online system (Puska et al., 2016). Thus, good quality content follows the legal obligations and increases the contributions to develop students' satisfaction and reuse intentions. To address the research gap, it is essential to respond to the following questions:

How the UTAUT factors ("performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC)") impact the users' MOOCs reuse intentions?

How perceived course quality affect users' MOOCs perceived satisfaction?

How perceived satisfaction directly affect users' MOOCs reuse intentions?

Is the mediating role of perceived satisfaction being critical for users' MOOCs reuse intentions?

This research's main goals are the application of the technology and quality factors to understand and predict the user's perceived satisfaction and reuse intentions toward massive open online courses usage. Therefore, a survey was developed to collect the primary data from students based in three public universities in Wuhan, China. This research tested the proposed hypotheses through PLS-SEM. This research reveals important theoretical contributions and provides guidelines to the instructional designers and instructors to develop effective strategies to make successful MOOCs learning through various online platforms.

To organize this research, first, we define a brief introduction, including the importance of the topic, research gap, and research questions. Then, we formulate the theoretical background and develop hypotheses, methodology, and analysis. Finally, we concluded this research with theoretical and practical contributions, also discuss the limitations and future research guidelines.

Literature Review

Theoretical Background and Hypotheses Development

This research's central theme is to test the UTAUT and quality factors' impact to predict users' perceived satisfaction and reuse intentions toward MOOCs usage. Figure 1 revealed the theoretical research model.

The UTAUT Model

According to Venkatesh et al. (2003), the UTAUT model mainly consisted of four factors "performance expectancy (PE), effort expectancy (EE), social influence (SI) and facilitating conditions (FC)," which determine the behavioral intentions and user behavior. Further, this model comprises four moderators (i.e., gender, age, voluntariness, experience). The UTAUT model has increasingly been applied in recent research, particularly in the technology context. Recent google scholar stats show more than 32,000 citations of the (UTAUT model) founding author Venkatesh et al. (2003). Thus, it reveals the importance of the UTAUT model. However, the application of the UTAUT model is still limited in the context of online courses. For example, Huang et al. (2014) concluded that MOOCs positively impacted the forum. Some other research studies revealed MOOCs' negative impacts on learning efficacy (Baxter & Haycock, 2014; Mak et al., 2010). Nordin et al. (2015) found positive results of all the UTAUT factors toward MOOCs. Fianu et al. (2018) found that performance expectancy positively influenced MOOC usage intentions in Ghana. Such inconsistency of findings leads to further investigation.

The UTAUT Factors

According to Venkatesh et al. (2003), the UTAUT model mainly comprised of four factors as 1) performance expectancy (PE), defined as “performance expectancy is the extent to which one believes that using a particular technology will enhance the user’s performance of a particular task(s)” 2) effort expectancy (EE) defined as “one’s perception of how easy or difficult a particular task can be performed” 3) social influence (SI) is “one’s conviction that people who are in your social circle, and are important to you, think that the use of a particular technology will be beneficial” 4) facilitating conditions (FC) is “one’s belief that there is enough technical and non-technical support from an institution to enable system use.” Prior research investigated the UTAUT factors in different perspectives, such as Nordin et al. (2015) investigated the UTAUT model in MOOCs perspective and found that performance expectancy helped the students learn about 74.6% with task completion 69.8% and increased their productivity 73% and enhanced understanding 74.2%. They found that effort expectancy positively impacted students’ perceptions by showing that interaction in using MOOCs was easy like 72.3%, skill enhanced 71.5%, easy to use 76.9%, and it was easy in learning about its usage 77.1% and further revealed that more than 50% respondents positively influenced toward MOOCs usage due to social influence. Similarly, lecturers and universities think that students should use MOOCs to enhance their knowledge. Finally, facilitating condition positively impacted the users’ intentions by revealing that more than 65% of respondents were agreed on having sufficient resources for MOOCs usage. Sattari et al. (2017) found that web-based training (WBT) acceptance positively affected performance expectancy, facilitating conditions, and medical students’ efforts expectancy. However, social influence was not affected the behavioral intentions of medical students. Mulik et al. (2018) collected data from 310 Indian students and found that effort expectancy, performance expectancy, facilitating conditions, and social influence significantly impacted students’ use intentions. Fianu et al. (2018) analyzed the 204 students’ data in Ghana and found that effort expectancy and social influence positively impacted MOOC usage intentions. However, performance expectancy and facilitating conditions did not affect MOOC usage intentions.

By following the UTAUT model factors, Chen and Hwang (2019) collected data from 312 students to analyze the students’ online learning behavior and found that effort expectancy and performance expectancy direct positively impacted student behavioral intentions in Taiwan. However, they did not find any impact of social influence on students’ behavioral intentions. Mahande and Malago (2019) evaluated the UTAUT model in e-learning in the Indonesian perspective and found that all four factors, performance expectancy, social influence, effort expectancy, and facilitating conditions, positively affect user behavioral intentions that lead to e-learning acceptance. Recently, Wan et al. (2020) found that effort expectancy, performance expectancy, and social influence positively impacted student continued intentions. However, facilitating conditions had no impact on students’ continued intentions. The above literature mainly revealed the investigation of behavioral intentions, and few studies predicted the continued or reuse intentions. Further, we found inconsistent findings related to the UTAUT model factors. Therefore, further research is required to investigate this topic and generalize the findings. We expect that the UTAUT factors positively contribute to users’ reuse intentions, especially in massive open online courses usage.

Performance expectancy is also related to user’s perceived satisfaction (Chan et al., 2010). Prior research used the UTAUT model to predict the users’ satisfaction in different industries and especially performance expectancy positively impacted the perceived satisfaction in mobile internet service (Thong et al., 2006), banking information system (Brown et al., 2008), and in the electronic patient record (Maillet et al., 2015). Although many studies applied the UTAUT model in massive open online courses perspective, but it still has limited application in satisfaction context, particularly in performance expectancy and perceived satisfaction. Thus, following prior literature, we expect that performance expectancy positively impacts user-perceived satisfaction. Thus, we develop the following hypotheses:

- H1: Performance expectancy positively impacts users’ MOOC reuse intention.*
- H2: Effort expectancy positively impacts users’ MOOC reuse intention.*
- H3: Social influence positively impacts users’ MOOC reuse intention.*
- H4: Facilitating conditions positively impact users’ MOOC reuse intention.*
- H5: Performance expectancy positively impacts users’ MOOC perceived satisfaction.*

Perceived Course Quality

Several different proposals have led to a quest for agreement on quality definition, such as compliance with requirements, value, or delighted expectations (Pozón-López et al., 2020). According to Camilleri et al. (2014), quality is not an objective entity but an amorphous concept. They proposed a conceptual map related to quality and educational context. Thus, they evaluated five concepts: efficacy, impact, availability, accuracy, and excellence for measuring quality. Similarly, dos Santos and Punie (2016) agreed on these five quality concepts in the educational learning context. According to Mohapatra and Mohanty (2017), institutions’ content quality and reputation are very important for students to use MOOCs. To confirm the positive effects of system quality on the learners’ use intentions, Lin and Lu (2000) found that some system quality factors still lead to internet use termination. Saeed et al. (2003) suggested that system quality is an important factor that positively impacts consumer perceptions that lead to favorable online behavior.

Contreras (2011) discussed that marketing scholars show a keen interest in examining the effects of quality on satisfaction because quality is essential for developing consumer satisfaction. Román et al. (2014) found that service quality positively affected satisfaction in an online environment. According to Hood and Littlejohn (2016), considering the complexity and operationalizing the

construct of quality dimensions, no accepted approach is available to measure the construct of quality. To examine the quality construct on student satisfaction in learning courses, Udo et al. (2011) suggested a SERVQUAL instrument by considering five dimensions: responsiveness, assurance, reliability, empathy, and website content. They found that except reliability, all these dimensions played important role in measuring perceived quality on satisfaction. Therefore, we assume:

H₆: Perceived course quality positively impacts users' MOOC reuse intention.

H₇: Perceived course quality positively impacts users' MOOC perceived satisfaction.

Perceived Satisfaction

Satisfaction is a critical construct in consumer behavior studies because satisfaction leads to continuously enhancing product usage, increasing profitability, and has a major effect on business performance. Perceived satisfaction be likely to use to evaluate the system's failure or success (Cigdem & Ozturk, 2016), especially in the system's reuse intentions context (Mohammadi, 2015). Some earlier research studies signify that satisfaction positively impacted technology use intentions in online courses learning perspectives (Alraimi et al., 2015; Joo et al., 2018; Shahijan et al., 2016). After the Covid-19 pandemic, very few studies investigated the perceived satisfaction on the MOOCs' continued intentions (Lu et al., 2019; Pozón-López et al., 2020). Previous research revealed that satisfaction found a positive mediator between quality e-learning and behavioral intentions in MOOCs perspective (Ayala et al., 2014; Udo et al., 2011), and similarly, satisfaction impacted positively between performance expectancy and continued intentions in mobile commerce (Marinković et al., 2020) and online food ordering through mobile applications (Alalwan, 2020). Thus, we assume the following hypothesis:

H₈: Perceived satisfaction positively impacts users' MOOC reuse intention.

H₉: Perceived satisfaction positively mediates between perceived service quality and users' MOOC reuse intention.

H₁₀: Perceived satisfaction positively mediates between performance expectancy and users' MOOC reuse intention.

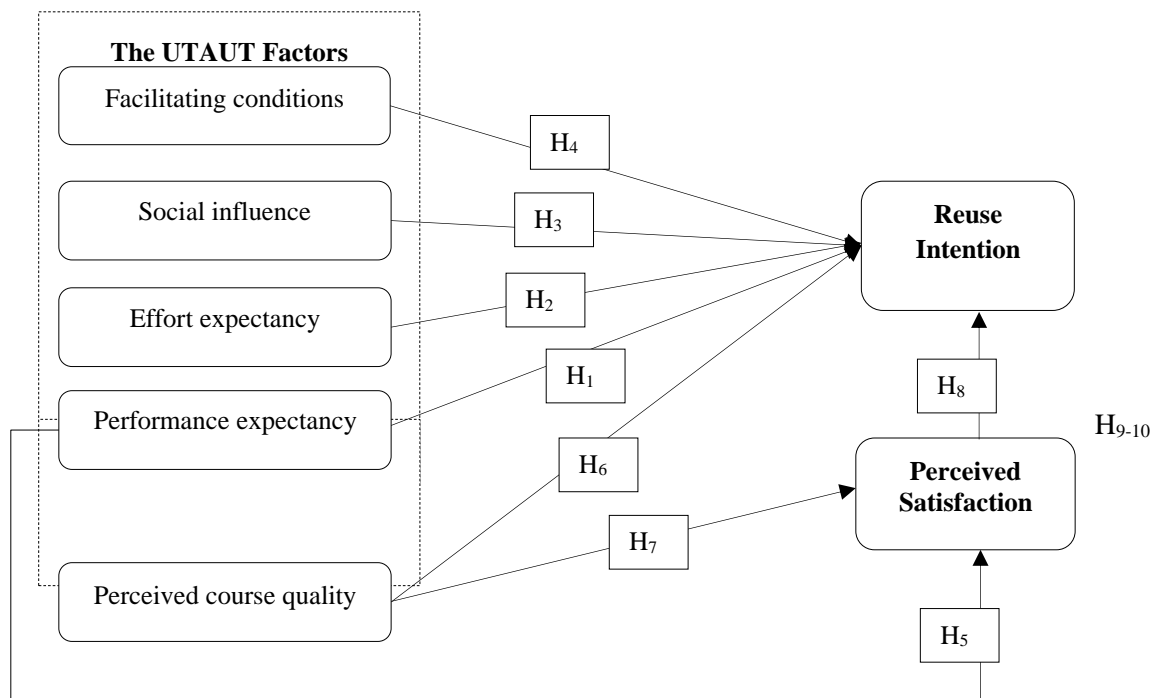


Figure 1: Theoretical Research Model

Research and Methodology

Instrument Design and Measures

A structured questionnaire was designed in three parts to achieve the research objectives. The first part contains the research objectives for users' understanding—the second part comprised questions of the constructs related to the theoretical model. We used four factors of the UTAUT model, performance expectancy and effort expectancy with four items each, social influence and facilitating conditions with three items each, and reuse intentions with three items were adapted from Chiu and Wang (2008). Perceived course quality with three items and perceived satisfaction with seven items were adapted from Pozón-López et al. (2020). All items were measured using seven points ("1=strongly disagree, 7=strongly agree") Likert scale. The third part consisted of

participant demographics. The questionnaire was designed in the English language. After preparing the questionnaire, 2 Associate Professors and five Ph.D. students reviewed the questionnaire. According to their guidance, we modified the questionnaire and finally posted on the <https://www.wjx.cn> (a leading Chinese survey website).

Sampling and Data Collection

Considering the research objectives, an online structured questionnaire was launched in three public universities in Wuhan, China. We mainly focused on students who were currently using massive open online courses. We used the convenience sampling technique as convenience sampling is an effective method to collect information in a timely manner (Safeer et al., 2020; Sekaran & Bougie, 2016). Further, similar research also used convenience sampling commonly (Al-Adwan, 2020). We collected data from 298 users who were using MOOCs. After data screening and removing biased responses, 283 responses were considered for SEM analysis. We followed the sample size (ten responses per question) proposed by Hair Jr et al. (2016). Thus, our sample size fulfilled the criterion. Users demographics displayed in the following Table 1.

Table 1: Users Demographics Profile

Description	Number	%
Sample Size	283	
Gender		
Male	220	77.70%
Female	63	22.30%
Age		
18 – 23	42	14.84%
24 – 29	119	42.05%
30 – 34	103	36.40%
35 – 40	19	6.71%
Education		
Bachelor	55	19.43%
Master	130	45.94%
Doctoral	98	34.63%
Annual Family Income		
\$3,000 - \$7,000	190	67.14%
\$7,001 - \$11,000	47	16.61%
\$11,001 - \$15,000	22	7.77%
\$15,001 - \$19,000	14	4.95%
Above \$19,000	10	3.53%

Analysis and Results

Partial least squares through structural equation modeling are commonly used and broadly accepted in statistical analysis and social sciences (Hair Jr et al., 2016). This study used PLS-SEM for testing the theoretical hypotheses by using SmartPLS 3 software (Ringle et al., 2015). When the research objectives contribute to theory and prediction of user behavior, PLS-SEM is the best fit analysis technique in this context (Hair Joseph et al., 2019; Hair Jr et al., 2016). Further, PLS-SEM is a casual predictive technique that focused on assessing models without considering data distribution assumptions (Sarstedt et al., 2017).

Initially, we reviewed and screened the raw data. All biased straight-lining responses and outliers were removed from the data. We did not find any missing value in data because we put restrictions on an online questionnaire to fill all questions. To check the normality, we analyzed the skewness and kurtosis values that were within range ± 1.96 (Hair, 2009). Our values met the criteria in all constructs. However, demographics values were out of range. Therefore, non-normality was observed in the data.

The Model Evaluation

The model evaluation has consisted of two parts. The first part evaluates through outer model measurement, and the second part evaluates through structural (inner) model measurement (Hair Jr et al., 2016).

The Outer Model Measurement

Outer model measurements include the constructs items' outer loadings, Cronbach's Alpha, rho_A, composite reliability, average variance extracted, and discriminant validity. According to Hair Joseph et al. (2019), the items' outer loadings, Cronbach's Alpha, rho_A, composite reliability (CR) must be more than 0.708, and AVE (average variance extracted) values should be higher than 0.50 the measure the outer model. However, outer loadings values between 0.708 to 0.95 are considered appropriate for model measurement. We ran the algorithm test and found that PS4 outer loading was more than 0.95 and had a collinearity problem (>0.5).

We removed the items PS4 and again retested the model. This time the results were according to recommended criterion. Table 2 explains all the results of constructs' outer loadings, Cronbach's Alpha, rho_A, CR, and AVE values, which fulfilled the criteria.

Table 2: Construct Internal Consistency Reliability and Validity

Constructs	Items	Loadings	Cronbach's Alpha	rho_A	CR	AVE
Performance Expectancy (PE)	PE1	0.862	0.908	0.911	0.936	0.784
	PE2	0.906				
	PE3	0.904				
	PE4	0.869				
Effort Expectancy (EE)	EE1	0.884	0.898	0.899	0.929	0.766
	EE2	0.882				
	EE3	0.887				
	EE4	0.848				
Social Influence (SI)	SI1	0.918	0.878	0.882	0.925	0.804
	SI2	0.908				
	SI3	0.863				
Facilitating Conditions (FC)	FC1	0.829	0.807	0.832	0.885	0.719
	FC2	0.833				
	FC3	0.881				
Perceived Course Quality (PCQ)	PCQ1	0.894	0.828	0.838	0.897	0.745
	PCQ2	0.890				
	PCQ3	0.802				
Perceived Satisfaction (PS)	PS1	0.884	0.938	0.938	0.951	0.763
	PS2	0.899				
	PS3	0.893				
	PS5	0.885				
	PS6	0.874				
	PS7	0.804				
Reuse Intention (RI)	RI1	0.931	0.926	0.926	0.953	0.871
	RI2	0.929				
	RI3	0.939				

After confirming the items' reliability and validity, we assessed the discriminant validity and found that all constructs' AVE values were greater than the maximum squared correlations of other constructs according to the recommended criterion by Fornell and Larcker (1981). Table 3 revealed that we had met this criterion. Later on, Henseler et al. (2015) criticized this traditional measure (Fornell-Larcker Criterion) and proposed a new method, Heterotrait-Monotrait Ratio (HTMT), to measure discriminant validity. Therefore we checked the discriminant validity through the HTMT technique and found that our results also met this criterion by following that all values were less than 0.90, according to Henseler et al. (2015) recommendation. Table 4 revealed the HTMT results.

Table 3: Fornell-Larcker Criterion

Construct	EE	FC	PCQ	PE	PS	RI	SI
EE	0.875						
FC	0.672	0.848					
PCQ	0.688	0.526	0.863				
PE	0.802	0.661	0.674	0.885			
PS	0.852	0.694	0.770	0.818	0.874		
RI	0.782	0.592	0.703	0.745	0.839	0.933	
SI	0.721	0.629	0.661	0.699	0.791	0.729	0.897

Table 4: Heterotrait-Monotrait Ratio (HTMT)

Construct	EE	FC	PCQ	PE	PS	RI	SI
EE							
FC	0.772						
PCQ	0.795	0.619					
PE	0.884	0.758	0.770				
PS	0.853	0.784	0.873	0.885			
RI	0.857	0.670	0.799	0.810	0.890		
SI	0.812	0.736	0.773	0.782	0.871	0.808	

The Structural (Inner) Model Measurement

According to Hair Jr et al. (2016), it is important to check constructs collinearity, coefficient of determination, predictive relevance (Q^2 value), and hypotheses assessment to understand the theoretical model's significance and relevance. First, we checked the collinearity by using the variance inflation factor (VIF). Hair et al. (2011) recommended that VIF values must be less than 5 in order to avoid multicollinearity problems in data. Our results found less than 5 values of VIF. Thus, there is no multicollinearity problem in our data. Second, we checked the explained variance R^2 (coefficient of determination) values to assess the model's predictive power. Researchers proposed the explained variance R^2 values 0.67, 0.33, and 0.19 reflected as a strong, medium, and weak theoretical model. Our results revealed variance explained R^2 value 0.757 (75.7%) on account of perceived satisfaction, and R^2 value 0.736 (73.6%) for MOOCs reuse intentions. Thus, our theoretical model explained strong predictive power. Besides the R^2 value, researchers also assess the Q^2 value to understand the model's predictive relevance. According to Hair Jr et al. (2016), the Q^2 should be greater than zero. Further, researchers recommended that Q^2 values 0.50, 0.25, and 0.00 explain the strong, medium, and small predictive relevance in the theoretical model. Our results found the 0.537 Q^2 value for perceived satisfaction and 0.599 Q^2 value for reuse intentions. Thus, our results explained the strong predictive relevance in the theoretical model.

Hypotheses Assessment

To assess the hypotheses, we used the BCA (bias-corrected and accelerated) bootstrapping technique using 5000 subsamples with two tails at 0.05 significance level (Chin, 1998; Hair Jr et al., 2016). The results revealed that performance expectancy has no effect on user MOOCs reuse intentions as PE \rightarrow RI ($\beta = 0.095$; $p = 0.141$). Therefore, H_1 was rejected. Other results explained that effort expectancy and social influence positively impacted users' MOOCs reuse intentions. Thus, hypotheses $H_2 - H_3$ were supported. However, facilitating conditions had non-significant impact on users' reuse intentions as FC \rightarrow RI ($\beta = -0.047$; $p = 0.339$). So, hypothesis H_4 was rejected. H_5 revealed that performance expectancy strongly affected users' perceived satisfaction as PE \rightarrow PS ($\beta = 0.548$; $p = 0.000$). Thus, H_5 supported. The results of H_6 explained that perceived course quality has no impact on users' reuse intentions. Therefore, H_6 was rejected. However, perceived course quality significantly impacted users' perceived satisfaction, and H_7 supported. It explains that users perceived satisfaction is more important before reuse intentions. Moreover, perceived satisfaction strongly impacted user reuse intentions as PS \rightarrow RI ($\beta = 0.453$; $p = 0.000$). Therefore, H_8 strongly supported (see table 5 for all results in detail).

Table 5: Hypotheses Testing Results

Hyp.	Constructs	Path Coefficient	Standard Error	95% Interval	Confidence Bias 2.5% 97.5%	t value	P-value	Support
Direct Relationships								
H ₁	PE \rightarrow RI	0.095	0.064	-0.024	0.225	1.473	0.141	No
H ₂	EE \rightarrow RI	0.190	0.075	0.042	0.335	2.544	0.011	Yes
H ₃	SI \rightarrow RI	0.134	0.059	0.021	0.251	2.273	0.023	Yes
H ₄	FC \rightarrow RI	-0.047	0.050	-0.146	0.046	0.957	0.339	No
H ₅	PE \rightarrow PS	0.548	0.055	0.436	0.649	10.027	0.000	Yes
H ₆	PCQ \rightarrow RI	0.097	0.065	-0.026	0.228	1.479	0.139	No
H ₇	PCQ \rightarrow PS	0.400	0.054	0.300	0.506	7.413	0.000	Yes
H ₈	PS \rightarrow RI	0.453	0.085	0.292	0.621	5.346	0.000	Yes
Indirect Relationships								
H ₉	PCQ \rightarrow PS \rightarrow RI	0.181	0.044	0.107	0.276	4.133	0.000	Yes
H ₁₀	PE \rightarrow PS \rightarrow RI	0.248	0.051	0.158	0.363	4.866	0.000	Yes

This research found that perceived course quality positively impacted users' MOOCs reuse intentions through perceived satisfaction as PCQ \rightarrow PS \rightarrow RI ($\beta = 0.181$; $p = 0.000$). thus, H_9 supported. Similarly, performance expectancy also positively impacted users'

reuse intentions through perceived satisfaction. So, H₁₀ was also supported. Figure 2 revealed that perceived course quality and performance expectancy had a direct non-significant impact on users' reuse intentions. However, these relationships become significant through perceived satisfaction. It explains that perceived satisfaction was fully mediated between perceived course quality, performance expectancy, and users' MOOCs reuse intentions.

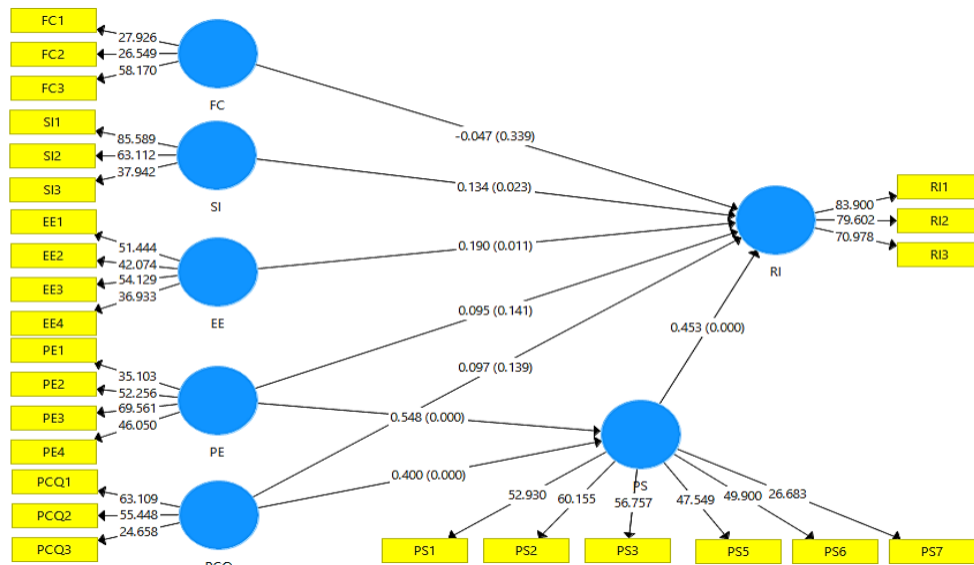


Figure 2: Hypotheses Relationships

Results and Discussion

This research revealed important findings that contribute to the theory and practical context. The hypothesis H₁ revealed that performance expectancy (PE) did not affect users' reuse intentions (RI). The finding is followed the prior similar research of Sharif et al. (2019), who found PE had no effects on user behavioral intentions. H₂ – H₃ found that effort expectancy (EE) and social influence (SI) positively impacted users' reuse intentions. Our findings are consistent with prior research of Wan et al. (2020), who found that EE and SI significantly predict the students continued intentions. Thus, EE and SI are essential factors that help to predict users' reuse intentions toward MOOCs. H₄ revealed that facilitating conditions (FC) had no impact on RI. The results are similar to earlier research that found that FCs were non-significant on user continued intention (Wan et al., 2020). H₅ revealed that PE significantly affected perceived satisfaction (PS). This finding followed prior research of Maillet et al. (2015), who found that PE is an essential factor for nurses' satisfaction. Thus, our research also found that PE is an essential factor for students' perceived satisfaction. The hypothesis H₆ explained that perceived course quality (PCQ) did not affect users' RI. However, this finding deviated from the earlier research of Yang et al. (2017). After the Covid-19, it may explain that along with PCQ, other factors are also important to influence the users' reuse intentions. H₇ – H₈ explained that PCQ positively affected the users' PS and RI toward MOOCs, and these findings are consistent with earlier research (Pozón-López et al., 2020). The H₉ – H₁₀ revealed that perceived satisfaction is a strong mediator between PCQ, PE, and users' RI toward MOOCs. Thus, our findings explain that satisfaction is a very important concern for students while using massive open online courses, especially during the Covid-19 pandemic.

Conclusions

This research's central theme was to investigate the technology and quality factors to predict users' perceived satisfaction and users' reuse intentions toward massive open online courses. Our results revealed that technology factors such as EE and SI directly impact users' reuse intentions while PE positively influences the users' reuse intentions through perceived satisfaction. Similarly, perceived course quality (SERVQUAL) also influenced the users' reuse intentions through perceived satisfaction. After the Covid-19 pandemic, technology factors are playing an important role in influencing users toward online courses. However, perceived satisfaction was a prime concern for users', especially by following good quality content, users can reuse the MOOCs. The technology developers and policymakers should consider improving their facilitating conditions, performance expectancy factors, and users' perceived satisfaction to regularly convince potential users to reuse massive open online courses.

This research contributed to literature effectively both in theoretical and practical aspects.

Theoretically, first, this study confirmed that EE and SI are important factors of the UTAUT model that influence the users' reuse intentions toward MOOCs. However, PE influences users' reuse intentions through perceived satisfaction, which explains that satisfaction is a key concern. Second, this study revealed that PCQ positively influenced users' reuse intentions through perceived satisfaction. It is also a significant contribution to understand user behavior. Third, this study found the critical role of perceived satisfaction in the current pandemic era.

Practically, this study provides essential guidelines for the developers and policymakers about massive open online courses. First, this study guides the developers and policymakers. They should improve their EE and SI factors to influence the users toward MOOCs use regularly. These EE can be improved by developing a user-friendly interface convenient to use, and SI can be improved by arranging different online campaigns on social media such as Facebook, Twitter, and LinkedIn. Second, PE is found a vital predictor to influence users' reuse intentions through perceived satisfaction. The technologists and instructors should introduce different communication campaigns that reveal the online unique course content, engaging, and user-friendly systems to enhance the users' perceived satisfaction. Finally, this study found that perceived course quality influenced the users' reuse intentions through perceived satisfaction. The findings help technologists and practitioners focus on the good quality course contents and target the relevant users by following different online communities to enhance their perceived satisfaction and convince them to reuse regularly. For example, they should introduce new good quality online business courses and focus on online business communities, which will help them attract these online communities to use the online system and regularly join business courses.

This research is not free from limitations and provides important guidelines for researchers to investigate the topic in future research. First, this study used convenience sampling in data collection. Therefore, future researchers should use random sampling with a larger sample size to generalize the findings. Second, this research did not use any moderator in the model. Future researchers may use the cultural variables as the moderator to contribute significantly. Third, this study found that PE, FC, and PCQ had no direct effect on users' reuse intentions. Future research may pursue to investigate these factors in different cultures to generalize the results.

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